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GAs versus Advanced Mathematical Tools for Optimizing the Allocation of Capital Renewal Funds in Large Infrastructure Networks

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Abstract: Civil infrastructure assets require continuous renewal actions to modernize the inventory and sustain its operability. Due to municipal infrastructure deficits and the diversity of existing assets, allocating limited renewal funds amongst numerous asset components represents a large-scale and complex optimization problem. To handle such problems, earlier efforts used GAs to optimize medium size problems, however, GAs suffer from steep performance degradation as problem size increases. In this paper, therefore, a segmentation process has been proposed to reduce problem size for individual problem segments. Despite the greatly improved GA efficiency achieved by the segmentation process, however, the processing time increases exponentially when model size increases. To optimize much larger problems and speed the processing time, this paper investigates the effectiveness of an advanced mathematical optimization tool, such as General Algebraic Modeling System (GAMS) and CPLEX. An optimization model has been developed and proved to outperform the GA model in large-scale scenarios. The paper discusses both the GA and the mathematical model and compares their results. The developments made in the paper present an effort to devise reliable decision support techniques to help asset managers standardize the fund allocation process and achieve substantial cost savings in capital renewal task.

Keywords: Capital Renewal, Asset Management, Genetic Algorithms, Life Cycle Cost Analysis, Network-Level Decisions

1 Introduction

Practical asset renewal plans are essential to cost-effectively preserve the value and performance of infrastructure assets. Optimizing renewal actions, however, is not a simple task due to municipal budget limits, the large number of diverse components, and the strict operational, environmental, and social constraints that should be taken into account. Due to these challenges, the expenditure backlog keeps increasing. For instance, in 2009, America’s infrastructure was estimated to have $2.2 trillion backlog, a 37% increase from 2005 (ASCE infrastructure report cards 2009). Effectively allocating limited renewal funds amongst numerous assets while considering different types of constraints is therefore an important task that involves a large-scale combinatorial optimization. Such problems are difficult to solve due to the exponential complexities associated with the number of possible combinations of possible solutions (i.e., solution space). A recent trend in solving such problems applies evolutionary optimization techniques such as Genetic Algorithms (GAs) (Liu et al. 2006; Elbeltagi et al. 2005). GA-based techniques are inspired by the improved fitness of natural selection and are capable of handling combinatorial problems by searching over the solution space. Although GAs have been used in different areas of engineering (Halfawy et al. 2005; Dridi et al. 2008; Ng et al. 2009; de la Garza et al. 2011), the solution quality and speed greatly depend on the manner by which a problem is modeled (Al-Bazi and Dawood 2010). In addition, increasing the number of variables and constraints significantly affects the optimization results and degrades the performance (Csiszár 2007; Hegazy and Elhakeem 2011). Modeling the asset renewal problems as a life cycle cost analysis (LCCA) is not a simple task and requires full consideration of operational level (asset-by-asset level) and also strategic (network-level) decisions (Hudson et. al. 1997). Even if a good LCCA is developed, genetic algorithms alone are not capable of handling large-scale problems and performance degradation becomes a major drawback, in addition to the unreasonable processing time. In addition, solutions obtained from GAs and other evolutionary systems are always questionable in terms of being global optimums (e.g., Thanedar and Vanderplaats 1995; Cook et al. 1997; Elbeltagi et al. 2005). On the other hand, although mathematical optimization techniques are capable of reaching globally optimum solutions, the performance of these techniques on large-scale combinatorial problems, specifically with complex and nonlinear relationships, is not consistent and they usually do not converge to a feasible solution. Mathematical optimization mechanisms such as branch-and-bound or branch-and-cut exhibit poor performance when the problem is more complex than what is known as easy-to-solve models, which are usually linear and binary formulations with simple relationships amongst parameters (W.L. Winston & M. Venkataramanan 2003; Wolsey. L. 1989).

Many researchers in the literature have introduced GA optimization models for life cycle analysis, maintenance, and renewal planning in different asset domains. Examples are: pavement maintenance (de la Garza et al. 2011; Ng et al. 2009); rehabilitation of water networks (Dridi et al. 2008); life cycle cost optimization of steel structures (Sarma and Adeli 2002); bridge maintenance (Elbehairy et al. 2008); building asset management (Hegazy and Elhakeem 2011); mixed municipal assets; and groundwater remediation (Zou et al. 2009). While these efforts provided useful life cycle cost models, little information has been reported on optimization performance on various problem sizes; and none has proved to be able to handle very large-scale problems that integrate both project-level and network-level decisions. To handle large-scale problems, one study by Sarma and Adeli (2002) was able to use a supercomputer to optimize the design of a 46-story steel building involving 3,300 members. Since the use of supercomputers is prohibitive, this paper, attempts to consider thousands of building components (i.e., close to 20,000) simultaneously using personal computers.

This paper provides an effective approach for arriving at near optimum solution to very large-scale problems by first properly formulating the problem then using two optimization approaches to enhance decisions: (1) using a segmentation approach to improve GA optimization results; and (2) using recently introduced advances in mathematical optimization techniques such GAMS and CPLEX. The results of both ‘GA + Segmentation’ and advanced mathematical optimization are then compared and discussed.

2 Capital Renewal Optimization Using Genetic Algorithm (GA)

Among the recent attempts to integrate component-level (often refer to as project level) and network-level decisions within a unified lifecycle cost analysis (LCCA) model is the Multiple Optimization and Segmentation Technique (MOST) developed by Hegazy and Elhakeem (2011). MOST handles medium-size problems by first optimizing individual component-level sub-problems and then using their results to formulate a network-level optimization, using genetic algorithm.

The model used in this study is developed upon MOST and at the component level (each component at a time) carries out individual small-scale optimizations for that component in each possible repair year over the planning horizon. Each small optimization determines the best repair method and cost for that component in that year. Within each small optimization, the formulation considers the component condition, deterioration behaviour, and expected after-repair condition to determine the repair with the highest benefit-to-cost ratio. The resultant of all component-level optimizations is a pool of best repair scenarios and their corresponding costs and benefits (Figure 1). The results of all the individual optimizations (optimal at the component level) are then passed to a single network-level optimization that is large in size, without loss of integration to decide on repair timing.

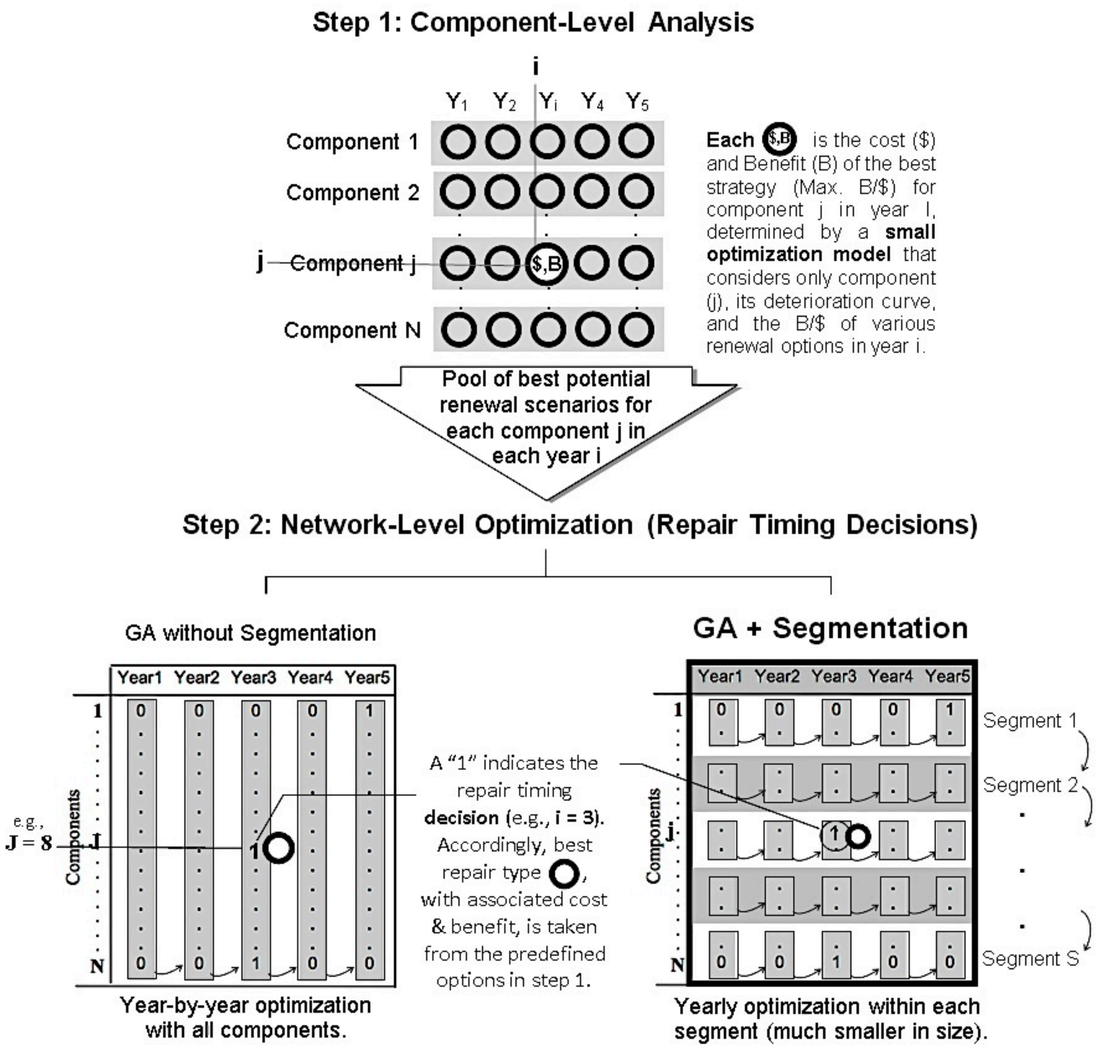

Figure 1: Integrated life-cycle optimization model

The objective of network-level optimization is to minimize the overall network deterioration index (DI_N) while not exceeding the available repair budget. Using the MOST technique, rather than a one-shot optimization over the 5-year planning horizon, a year-by-year optimization formulation (step-wise formulation) is used from the first year consecutively until the end of planning horizon (bottom left of Figure 1). Using this formulation reduces the solution-space size and leads to a better solution quality. In general, the overall parameters in the network-level optimization (variables, objective function, and constraints) are as follows:

Decision Variables: being $Y_{11}, \dots, Y_{jk}, \dots, Y_{n5} = 0 \; or \; 1$
where, Y_{jk} = 0 (no repair), Y_{jk} = 1 means component *j* is decided to be repaired in year *k*, and n is the number of components.

Objective function: minimize the network deterioration index (DI_N), which is the weighted average of all components' conditions in all years, weighted by the components' relative importance factors (RIFs).

Constraint: Total repair cost for the components selected in year $k \leq$ budget limit in year k.

Figure 2 depicts the spreadsheet-based life cycle cost analysis (LCCA) model. The model is developed for the Toronto District School Board (TDSB), which administrates a large network of school building assets. Considering the highlighted component (e.g., a specific window in school number 3), if it is repaired in year 3, its deterioration will be reduced from 72.49 to 24.31 (available from the component-level analysis) at a cost of $12,100. The decision to repair the highlighted component in year 3 is selected by assigning a value of 1 to the decision variable of year 3 (as shown). Accordingly, the LCCA model reads values for relative importance; expected performance after repair in year 3; and repair cost. The combination of network-level decisions determines the overall network deterioration index (DI_N). The GA tool used is an efficient commercial software (EVOLVER), which is used in all GA experiments in this study. Using GA alone, the model was able to handle network-level problems of up to 8,000 components (one building has about 150 components) simultaneously, as compared to simple ranking results.

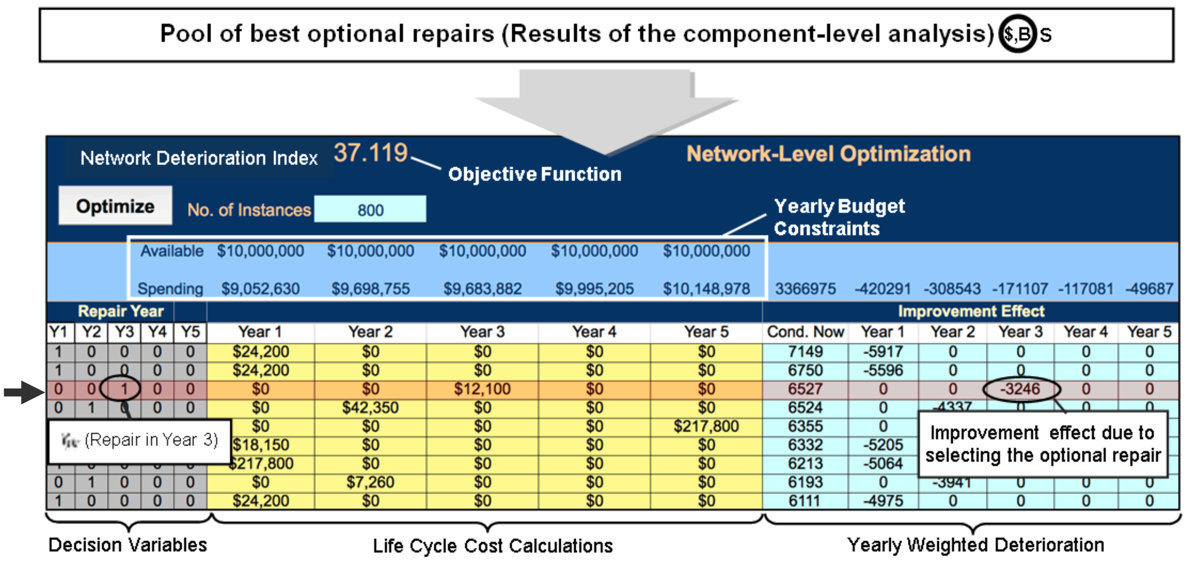

Figure 2: Network-level life cycle cost analysis model

Although GAs proved to be effective in many cases, they can lose their efficiency when the problem size becomes large (Csiszár 2007). The performance of the MOST technique as discussed previously is an example of GAs' steep performance degradation. To increase the efficiency of GAs, therefore, a segmentation method has been proposed as a supplementary mechanism that effectively improves the GA solution quality in asset renewal problems (Hegazy and Rashedi 2012). The 'GA + Segmentation' mechanism (bottom right of Figure 1) breaks down the large-scale network-level optimization model into smaller sub-problems (i.e., segments) and optimizes them separately through a GA-based optimization procedure. The created sub-problems are easier to optimize due to their reduced solution space size, less number of variables and constraints, and also because of the applied step-wise binary (year-by-year) formulation. After implementing the GA+Segmentation process on the LCCA model of Figure 2, different size problems were then created using randomized multiple copies of the base 800-component data of the TDSB. This approach benefits the comparison since the results should be multiples of the best results obtained from the 800-component case. The GA+Segmentation was able to improve the solution quality significantly with 27% improvement over the GA without segmentation approach, and exhibited very low performance degradation on larger size problems. The GA+Segmentation proved to be very effective in handling very large-scale problems, however, it has two drawbacks. First, its processing time exponentially increases when the problem size increases and second is that the results are not globally optimum. In asset renewal problems, even a small improvement in the result is analogous to considerable improvements in spending. Thus, finding a close to global optimum solution is very beneficial to asset managers and engineers.

3 Capital Renewal Optimization Using Advanced Mathematical Tools

In an effort to examine better ways to reach close to global optimum solutions fast, software from a new bread of mathematical optimization tools has been tested. Advanced tools such as GAMS or IBM ILOG CPLEX optimizer are claimed to be capable of modeling and solving complex problems using their sophisticated solver engines. The General Algebraic Modeling System (GAMS) is a high-level modeling system for mathematical programming and optimization. It consists of a language compiler and an array of integrated high-performance solvers. GAMS is tailored to complex, large scale applications and allows users to build large maintainable models that can be adapted quickly to new situations (GAMS user guide 2010). GAMS provides a high-level programming and modeling language to mathematically model different types of optimization problems. Once the model is written in GAMS language, different built-in solvers can be used to execute the optimization. For large-scale asset renewal problems one of its powerful solvers, CPLEX, has been utilized in this study. The CPLEX optimizer is mostly applicable to difficult linear, quadratically constrained, and mixed integer programming problems, which fits the characteristics of the asset renewal problem. CPLEX uses enhanced branch-and-bound methods combined by a dynamic search to solve IP problems by generating LP sub-problems in which the integer constraints are relaxed into continuous models (CPLEX User Guide). If the solution obtained from a sub-problem is an integer solution, it is a candidate for being the optimal solution to the problem (W.L. Winston & M. Venkataramanan 2003). After solving all sub-problems, candidate solutions with integer results are compared and the optimal solution is obtained based on the direction of the optimization (minimization or maximization). Due to the huge amount of calculations required for large number of sub-problems, processing time can be large, except when the problem is appropriately formulated as a "strong formulation" or "easy-to-solve model" (Wolsey. L. 1989). Some of the key elements of a strong (easy-to-solve) IP formulation include (Wolsey. L. 1989; Winston & M. Venkataramanan 2003): linearity of objective function; low range of variations in decision variables; and simple relationships among variables; constraints; and objective function. The mathematical formulation considers N asset components, with the year of repair for any component (j) being represented by a binary variable along the 5-year plan. This formulation includes linear equations, minimum range of variable variation, without any complex interrelationships. The objective function is accordingly defined as follows:

$$[1] \quad \text{Minimize } \mathrm{DI_N} = \frac{\sum_{j=1}^{N}(EP_{j0}\times RIF_j) \; + \; \sum_{\mathrm{j=1}}^{\mathrm{N}}\sum_{\mathrm{k=1}}^{\mathrm{t}} \mathrm{Y_{jk}\times IE_{jk}\times RIF_j}}{\sum_{\mathrm{i}} \mathrm{RIF_j}}$$

where, RIF_j is the relative importance factor (0 – 100) of component *j*; N is the size of the network; and EP_{jk} is the expected performance of asset j after repairing in year k, which is calculated by taking the average of the deterioration indices (DI_{ij}) after repair at year k over the planning horizon. IE_{jk} is the improvement effect of repairing asset j in year k, and is calculated as follows:

$$[2] \quad \mathrm{IE_{jk} = EP_{jk} - EP_{j0}}$$

In the presented case study only a single visit, is allowed for each component during the planning horizon). Also the yearly spending must be less than the available annual budget.

$$[3] \quad \text{For } \mathrm{k = 1 \text{ to } t} \qquad \sum\nolimits_{\mathrm{j}} \mathrm{Y_{jk}\times IRC_{jk} \le B_k}$$

$$[4] \quad \text{For } \mathrm{j = 1 \text{ to } N} \qquad \sum\nolimits_{\mathrm{k}} \mathrm{Y_{jk}} \le 1$$

The mathematical formulation (including all relationships for deterioration, expected performance, and repair costs) has been coded in GAMS language, with different links to the row data in Excel. Input data are linked to GAMS by using GAMS Data Exchange (GDX) files (Figure 3). Once the model was created, the CPLEX was selected by GAMS as the solver engine and after the optimization was carried out, the results were exported back to the spreadsheet-based model to be analyzed. Different GAMS/CPLEX models were generated for different size problems. Based on the results obtained, the GAMS models were able to reach globally optimum solutions for large-scale problems in very short processing time (less then 5 minutes) with no performance degradation. As shown in Figure 4, using GAMS/CPLEX is was possible to improve upon simple ranking results by around 30% while optimizing problems with more than 20,000 components. The figure also shows that applying both GA+Segmentation and mathematical approach solved the problem of performance degradation due to problem size increase. It is important to note that although the results of the mathematical approach are better than those of the GA+Segmentation approach (see Figure 4), the latter can still be very useful, particularly for nonlinear and more complex problems that are more difficult to model.

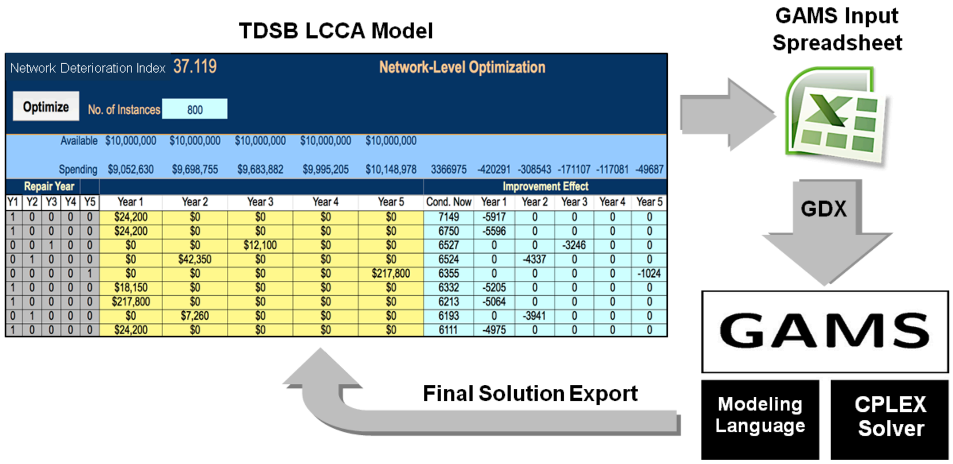

Figure 3: Optimization procedure using GAMS/CPLEX

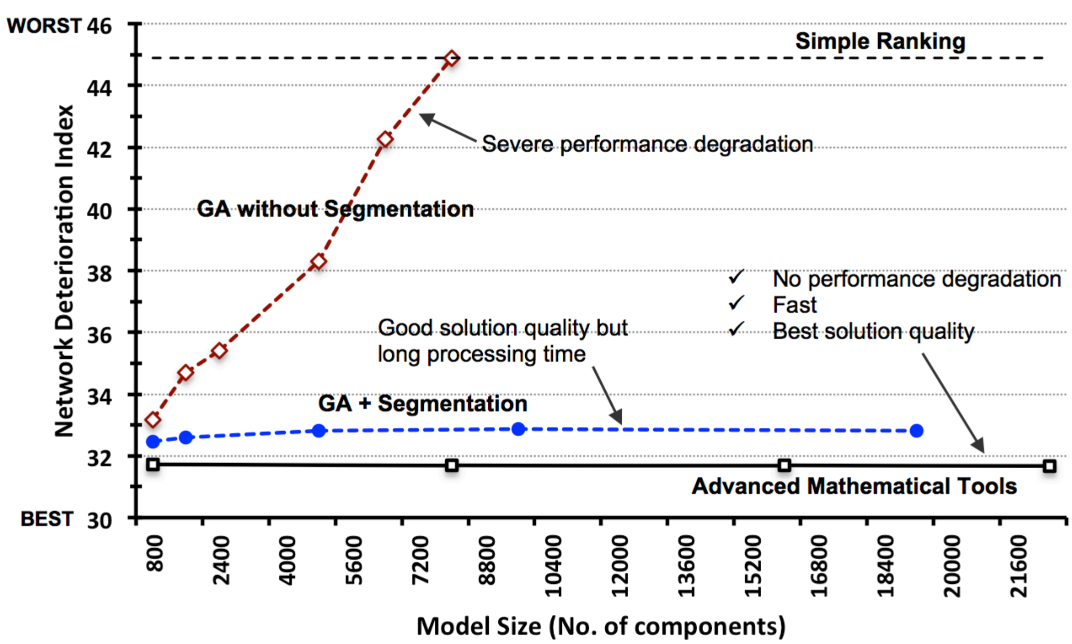

Figure 4: Optimization results and comparison

4 Concluding Remarks

This paper investigated and compared the processing time and performance of advanced mathematical optimization tools (GAMS/CPLEX) versus modified GA-based optimization techniques for large-scale asset renewal problems. First, a GA+Segmentation approach was used on larger size problems (20,000 components). While solution quality was high and performance degradation was avoided, processing time shows exponential increase with problem size. In an effort to optimize much larger models fast and with better quality solutions, a GAMS/CPLEX model was developed. The powerful optimization engine of CPLEX proved to be able to handle large size problems. Based on various experiment on different size problems, application of advanced mathematical tools combined with the effective modeling improved solution quality and speed. Yet the GA+Segmentation technique is still a valid mechanism for handling complex large-scale problems that cannot be modeled as an easy-to-solve formulation. The models presented in this paper can be adapted to other asset domains to support fund allocation decisions, and ultimately to improve the economics of the costly capital renewal programs.

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